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# A Minimum Cloud Cover Mosaic Image Model of the Operational Land Imager Landsat-8 Multitemporal Data using Tile based

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**ABSTRACT**

The need for remote sensing minimum cloud cover or cloud free mosaic images is now increasing in line with the increased of national development activities based on one map policy. However, the continuity and availability of cloud and haze free remote sensing data for the purpose of monitoring the natural resources are still low. This paper presents a model of medium resolution remote sensing data processing of Landsat-8 uses a new approach called mosaic tile based model (MTB), which is developed from the mosaic pixel based model (MPB) algorithm, to obtain an annual multitemporal mosaic image with minimum cloud cover mosaic imageries. The MTB model is an approach constructed from a set of pixels (called tiles) considering the image quality that is extracted from cloud and haze free areas, vegetation coverage, and open land coverage of multitemporal imageries. The data used in the model are from Landsat-8 Operational Land Imager (OLI) covering 10 scenes area, with 2.5 years recording period from June 2015 to June 2017; covered Riau, West Sumatra and North Sumatra Provinces. The MTB model is examined with tile size of 0.1 degrees (11x11 $km^2$), 0.05 degrees (5.5x5.5 $km^2$), and 0.02 degrees (2.2x2.2 $km^2$). The result of the analysis shows that the smallest tile size 0.02 gives the best result in terms of minimum cloud cover and haze (or named clear area). The comparison of clear area values to cloud cover and haze for three years (2015, 2016 and 2017) for the three mosaic images of MTB are 68.2%, 78.8%, and 86.4%, respectively.



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## 1. INTRODUCTION

The need for remote sensing image mosaic of minimum cloud cover for wide area analysis, such as provincial level, is now increasing, it is in line with the increase of national development activities that implement one map policy as stated in the Laws [1], among others Law No. 4 of 2011 on geospatial information [2], and Law No. 6 of 2014 on the village [3]. However, the continuity and availability of medium resolution Remote Sensing data in Indonesia for the purpose of monitoring natural and environmental resources is still low, moreover for the areas often covered by cloud and haze, such as Sumatra, Kalimantan and Papua [4], [5].

Meanwhile, LAPAN as the Institution assigned to provide annual remote sensing data with minimum cloud cover and cloud free for all Indonesian territory, and the provision of information related to the image quality [6], has not yet continuously provided such data. This is because until now there has been

no standardization policy data processing mosaic of remote sensing image of medium resolution. According to Law No. 21 of 2013, LAPAN is also tasked to set the nationwide standardization of data and product quality, namely information and methods of processing of remote sensing. For the purpose of rapidly and consistently monitoring analysis, it is required image mosaic generated by using algorithms that do not change the reflectance value, that is the reflectance image mosaic (RIM).

Several image mosaicing algorithms for the purpose of a digitally land resources monitoring analysis have been developed by previous researchers. They do pre-processing with several steps of radiometric corrections/normalization and cloud/haze removal with algorithms to be applied automatically or semi-automated with complicated steps and time-consuming procedures. In the selection of the best data to be representative of data on mosaicing process, several researchers used mosaic scene based approaches (MSB) [5], [10-16], and other researchers developed mosaic pixel based approaches (MPB) [17-22]. In addition, the area has a relatively various complete and topography, from flats to mountainous. The area also has a relatively complete object of land cover, consisting of forests, plantations, settlements, shrubs, bushes, and rice fields to mangroves. The dynamics of land use/cover changes in this area are quite dynamic and can be as representing a land cover change analysis area [17], [23-26].

In order to provide cloud free or minimum cloud covered images of the entire territory of Indonesia, a fast algorithm or data processing model is needed to produce cloud cover free or minimal cloud cover mosaic, either for visual analysis (visual mosaic or color balancing mosaics) or for digitally monitoring analysis. The objective of this paper was to develop a model of remote sensing data processing for Landsat-8 Operational Land Imager (OLI) to obtain the annual minimum cloud cover or cloud free and haze mosaic image with tile based model algorithm, covering (1) formulation of the MTB model; (2) application of MTB model using Landsat-8 OLI; (3) comparison analysis of image of MTB and MPB model results; and (4) statistical analysis of MTB model.

In addition, the MTB algorithm provides a quality assessment of each tile, based on the best value, derived from the maximum percentage of pixels from the cloud free area, haze free area, vegetation coverage, and open land coverage from a multitemporal collection of images. The model proposed in this paper was to simplify the pre-processing steps, particularly radiometric corrections/ normalization such as TOA (Top of Atmosphere) and the BRDF (Bi-directional Reflectance Distribution Function) only, while the cloud and haze elimination, and the assessment of tile quality as the whole mosaic was completed by using mosaic tile based approach (MTB). The results of this paper were expected to be an input or policy brief to develop the policy [6]. Mosaic images were widely used, although they have been generated through digital processes such as color balancing processes [7-9], but designation is still oriented to the analysis visually or manually.

## 2. TYPES OF IMAGE MOSAICS

According to Law 21/2013 article 15 paragraph 2 [6], it is mentioned that the process data are ready data from the primary data processing, while the primary data is raw data received directly by the ground station. Mosaic image data discussed in this paper either as input or output is categorized as the process data. The process data used in the study are Landsat-8 OLI corrected geometric precision terrain-corrected Level-1T or (L1T) or systematic terrain-corrected Level-1GT (L1GT) [27]. The resulting mosaic image becomes process data to be processed, interpreted, analyzed for further information extraction.

The Landsat-8 process data can be further analyzed visually using color balancing mosaic (CBM), or digitally using reflectance image mosaic (RIM) [9]. CBM is an image of mosaic process results that can be interpreted visually based on key interpretations such as tone, color, pattern, texture, shape, size, site, shadow, and association. While RIM is intended primarily for digital analysis based on the reflectance number of each pixel. Based on tile size, RIM type can be divided into MPB (Mosaic Pixel Based), MTB (Mosaic Tile Based), and MSB (Mosaic Scene Based).

The Position of Mosaic Tile Based (MTB) compared to the previous mosaicing models of Reflectance Image Mosaicing such as MSB and MPB is shown in Figure 1. From the Figure 1 shows clearly that the MTB is the continuation models of MPB. The principal differences between these two types of image mosaics CBM and RIM were shown in Figure 2.

The CBM was characterized by pan-sharpening product, developed with commercial software, semi-automatic algorithm, more seamless, with subjective and limited quality of information, high spatial resolution (15 m), and more suitable for visual analysis. While the RIM was characterized by full band multispectral product, developed by open source software, automatic algorithm, the seamless depend on the scale, with more quality of information, lower resolution (30 m), and suitable for digital analysis [21]. The MPB model is a pixel-based approach that meets the best requirements of multitemporal data sets in a certain period. And the MTB model is an approach that is set up from a set of certain sizes of the best tiles of

multitemporal data sets. While the MSB is an approach based on the best collection of scenes, cloud free or minimal cloud cover from multitemporal data sets.

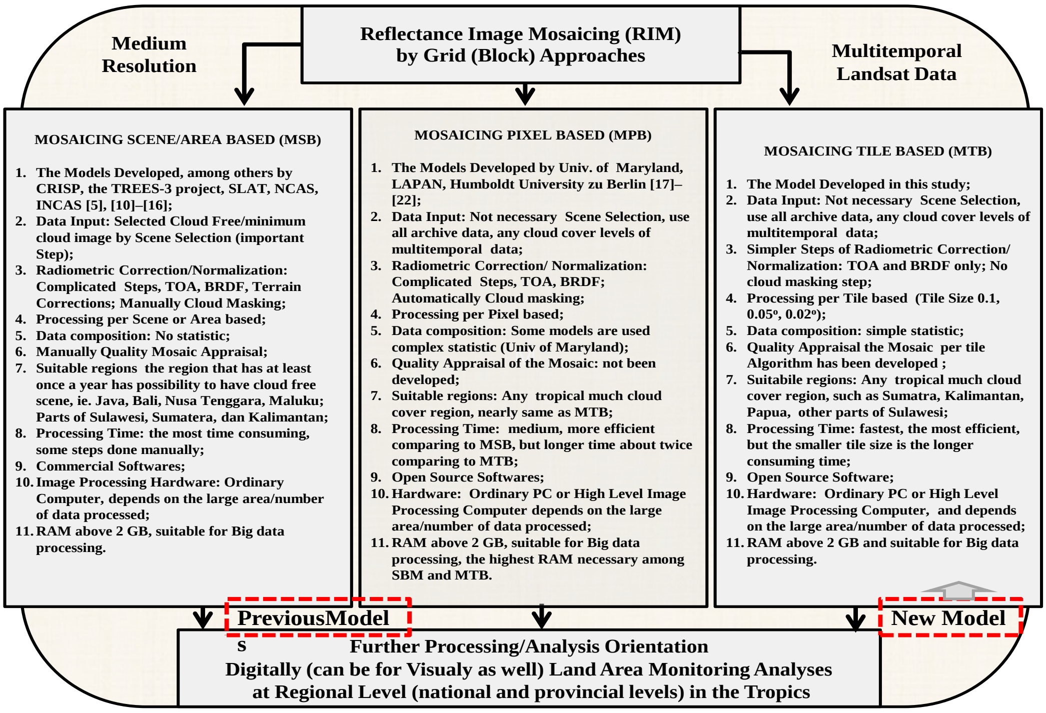


Figure 1. The position of mosaic tile based among previous mosaicing models

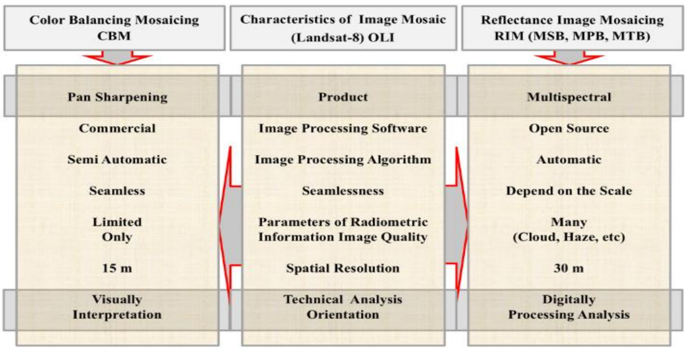


Figure 2. The characteristics of color balancing mosaicing and reflectance image mosaicing techniques, adopted from [21] with modifications

MPB and MTB models are more suitable for mosaicing in areas that were often or even covered in clouds and hazes throughout the year, such as Papua, some parts of Kalimantan and Sumatra. While the MSB model was more suitable for mosaicing in regions that have the possibility to obtain a clear image within a year, such as the islands of Java, Bali, Nusa Tenggara, and Maluku [5]. Ideally, geometric correction also includes correction of slope or terrain correction. However, the selection of both radiometric corrections, already meet the minimum standards of the process, but it was also intended to simplify the radiometric correction steps. This paper will only examine the mosaicing using MPB and MTB approaches.

### 2.1. Model Mosaic Pixel based (MPB)

This paper was focused on minimum cloud cover mosaic image of the OLI Landsat-8 multitemporal data for the purpose of land area analysis, especially vegetation related analysis. There were 6 (six) MPB

approach algorithms for land area analysis, namely Maximum NDVI, formula (1); Maximum Reflectance Numbers of NIR, SWIR devided by Green Bands Index, a formula (2); Maximum Reflectance Numbers of NIR devided by Green Bands Index, a formula (3); Maximum Reflectance Numbers of SWIR devided by Green Bands Index, a formula (4); Minimum Reflectance Number of Red Band, formula (5); and Minimum Haze Index, a formula (6);

$$\text{MaxNDVI}(i,j) = (\text{INIR}(i,j) - \text{IRed}(i,j))/(\text{INIR}(i,j) + \text{IRed}(i,j)) \quad (1)$$

$$\text{MaxNIR, SWIR\_Green}(i,j) = \text{Maximum}(\text{INIR}(i,j), \text{SWIR}(i,j))/\text{IGreen}(i,j) \quad (2)$$

$$\text{MaxNIR\_Green}(i,j) = \text{INIR}(i,j)/\text{IGreen}(i,j) \quad (3)$$

$$\text{MaxSWIR\_Green}(i,j) = \text{ISWIR}(i,j)/\text{IGreen}(i,j) \quad (4)$$

$$\text{MinRed}(i,j) = \text{IRed}(i,j) \quad (5)$$

$$\text{MinHI}(i,j) = (3.2 * \text{IBlue}(i,j)) - \text{IRed}(i,j) \quad (6)$$

Where:

NDVI: Normalized Difference Vegetation Index; Ibx(i,j): reflectance band bx, in the row column (i,j); NIR: Near InfraRed; SWIR: Short Wave InfraRed; Blue, Green, Red : Blue, Green, Red Bands; HI: Haze Index.

Before merging multiscene mosaics on the MPB model, a multitemporal mosaic per scene was processed. The study area was covered by 10 (ten) scenes of the Landsat data. Spectral bands used were band-2 to band-6 with a spatial resolution of 30 meters, that is suitable for land assessment, mainly vegetation-related analysis. The experimental implementation of the MPB model for this paper area was conducted using 5 (five) dataset groups, namely the data group of a half (0.5) years, one (1) year, one and a half (1.5) years, two (2) years, and two and a half (2.5) years as shown in Figure 3. Each group of data will be analyzed the cloud cover and haze clearness levels.


Figure 3. The periods of dataset groups for MPB experiment

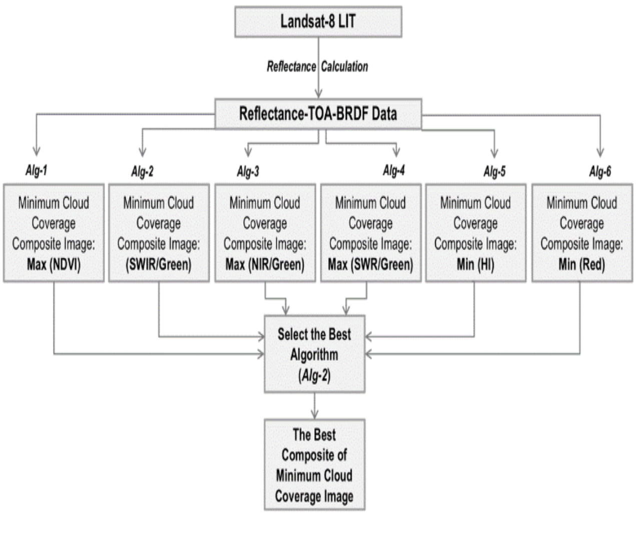


Figure 4. Algorithm of the development of mosaic pixel based (MPB), adopted from [21] with minor modifications

It was assumed that the longer the time period of dataset used the higher achieving minimal cloud cover even cloud free. The image quality of MPB processing results of various time periods were analyzed qualitatively and descriptively. Only 2 (two) main parameters of image mosaic quality that was cloud cover and haze conditions were analyzed from the image display of band combination images of RGB 432 and

RGB 654. The processing steps of the MPB mosaicing in this paper were presented in Figure 4. The results of the MPB model were shown by RGB color composites of bands 432 and 654.

### 2.2. Model Mosaic Tile based (MTB)

The MTB model was developed based on the results of the MPB and MSB evaluation that have been developed [21], and refers to the models of University of Maryland (UM) [17], [19], [20], [26] and Australian National Carbon Accounting System (NCAS) [13], as well as Indonesia National Carbon Accounting System (INCAS) [5]. The processing steps of mosaicing with a MTB model in this paper were presented in Figure 5. The results of the MTB model were also shown by RGB color composites of bands 432 and 654.

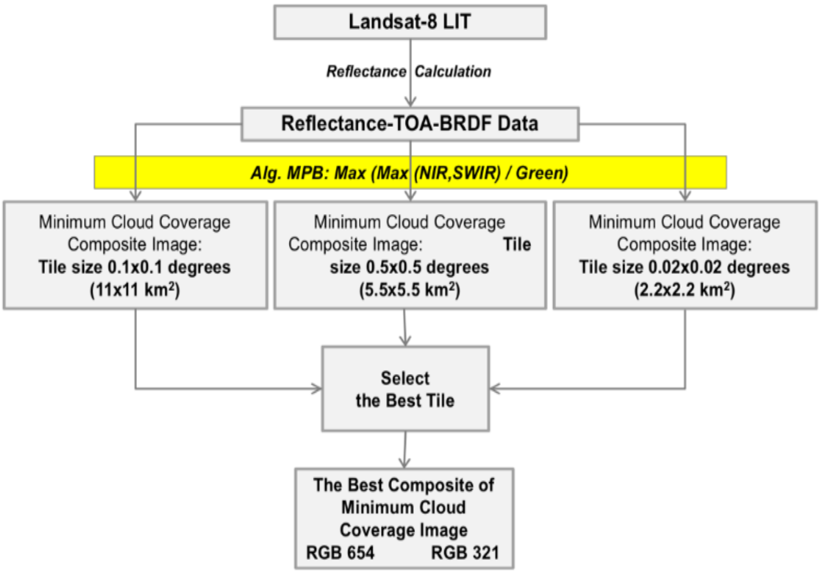


Figure 5. Algorithm of the development of mosaic tile based (MTB)

In the MPB model, the remaining cloud cover on the completed process of multitemporal mosaic image will be difficult to improve the result, as its image mosaicing was based on the pixel approach. While on the MTB model, improvements of the mosaic image results be done by improving and correcting the cloud cover on the bad tiles. The following algorithm was used to assess whether the tile from the mosaicing process was good or still needs to be improved. The principle of the algorithm for improving cloud cover on the tile was to reduce the size of the tile.

The quality of each tile in percent (%) in the mosaic image can be analyzed using a simple IoCVO (Index of Clear, Vegetation and Open Land) algorithm as shown in formula (7).

Final_score=a*%Cloud Free+b*%Haze Free+c*Veg. Conv. +d*Open Land Conv (7)

Where:

a. % Cloud Free is the percentage of brightness value or free from cloud cover on image tile; range of value between 0-100%; 100% value if the tile of cloud free image, and value 0 when the total image tile is closed by cloud;
b. % Haze Free is the percentage of brightness or free value of haze on the image tile; the range of values between 0-100%; haze value 100 if the image tile is absolutely no haze, and value 0 if the image tile is completely fogged;
c. Veg. Con. (Vegetation Confidence) is the percentage of a confidence value of the vegetation cover on the image tile, derived from the mean NIR/Green index value on the land; the range of values between 0-100%;
d. Open Land Con. (Open Land Confidence) is the percentage of a confidence value of the open land on the image tile, which is derived from the average SWIR-1/Green index value of the land; the range of values between 0-100%; and
e. a, b, c, d are coefficients given the value 1.

Unlike the MPB model approach, in the MTB model approach the data were grouped based on 3 (three) tile sizes. Considering of the size of overlapping of two Landsat image scenes, three trial tests with tile sizes of 0.10x0.10 degrees (~11kmx11km) consists of 400x400 pixels; 0.05x0.05 degrees (~5.5kmx5.5km) consists of 200x200 pixels, and 0.02x0.02 degrees (~2.2kmx2,2km) consists of 80x80 pixels have been done. An illustrative comparison of the difference in size and number of tiles on MTB processing in the study area was shown in Figure 6.

The image processing results of MTB model with three tile sizes, was analyzed their quality of mosaic, cloud cover, and its haze. The result was assumed that the smaller the tile size will be the greater the number of record tiles, and the higher the quality of the mosaic. The image results from MPB and MTB models were compared to analyze the advantages and disadvantages of its result. Then the image results of MTB model were analyzed by the percentage of cloud coverage and haze to conclude the quality of the image produced.

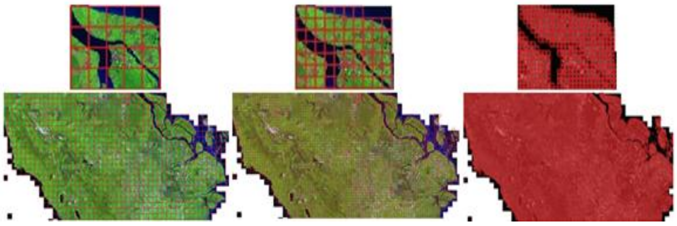


Figure 6. Illustration of image data tiling in study area

## 3. RESULTS AND DISCUSSIONS

### 3.1. Color Balancing Mosaic (CBM)

Figure 7 shows a quick look (QL) of CBM mosaic image with RGB 432 multitemporal data composition in 2016 and 2017. The mosaic image on the left shows more blurred than the right image. After the image enhancement through the stretching histogram, the results which were shown on the right image look clearer and more contrasty.


Figure 7. Color balancing mosaic images of RGB 432

The results of the CBM Natural Color Combination of RGB 432 Landsat-8 data of 2016 and 2017 look seamless, no line or a sign indicating that the image was generated from several different path-row scenes or different time recording. However, the mosaic image was only used for visual analysis, since the image was a color balancing product on the image that has been done histogram adjustment to the image intensity value on each band. The process was dedicated to the ease of visual interpretation, and cannot be used for digital interpretation because its reflectance value does not reflect the original value of the reflectance.

The advantages of the CBM product were the appearance of the image looks seamless, both in natural color (RGB 432), even more in the image of vegetation analysis (RGB 654). The visual seamless rate of this product is highest among the various mosaic products, processed using today's emerging software. In addition to seamless, processing with this algorithm can also eliminate clouds automatically. This CBM

processing, in terms of time required for data mining and data processing was relatively fast, and the procedure steps were relatively practical, because the processing was automatic. The Landsat-8 image can also produce 15-meter CBM products utilizing a panchromatic band.

### 3.2. Mosaic Pixel Based (MPB)

In the MPB model approach, before spatial multiscene mosaic processing, a multitemporal mosaic per scene was processed first. There were 10 (ten) scenes image covered the study area. The band selection used was the appropriate band for the analysis of terrestrial areas, mainly related to vegetation, covering band-2 to band-6 having a spatial resolution of 30 meters.

The study with the MPB model was conducted using 5 (five) data sets, that was half-year (with 10-12 data acquisition), one year (with 12-23 data acquisition), one and a half years (with 32-35 data acquisition), two years (with 34-38 data acquisition), and two and a half years (with 46-50 data acquisition) data group.

Each group of data consisting of a number of scenes observed its clearness from cloud cover and haze. The longer the time-range of data used, the higher the opportunity of obtaining cloud-free and haze mosaic image. Figure 8 shows an example of intermediate results, multitemporal mosaic per block of one degree size (110x110km$^2$) before merging into a whole mosaic. Those blocks were used as the input for multiscene spatial on MPB mosaicing. The resulted mosaic contains fully 5 (five) band images, which can be further analyzed.

From image mosaic analysis processed by the MPB model with annual data variations, as shown in Figure 9, it can be concluded that the 2016 image looks relatively clear and found only a little haze and cloud rather than the 2015 and 2017 images, which was shown in the red circle mark. Its indicate that there was a clear pixel of at least one or more of the data sets used, meaning that the weather conditions in the study area of the year have been relatively clear.

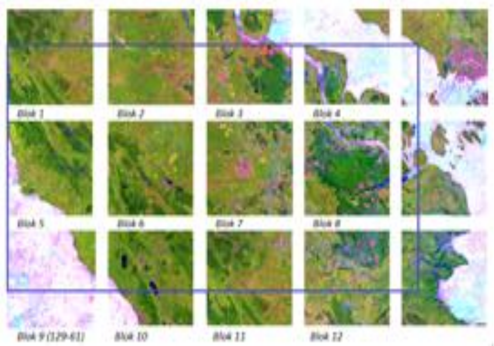

Figure 8. Per block MPB mosaic image (10 scenes of January-June 2017 dataset)

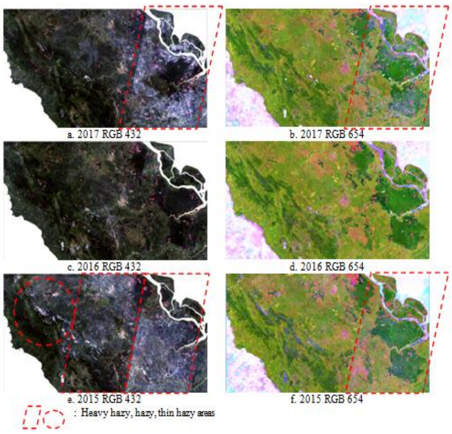


Figure 9. QL of annually mosaic pixel based image (MPB)

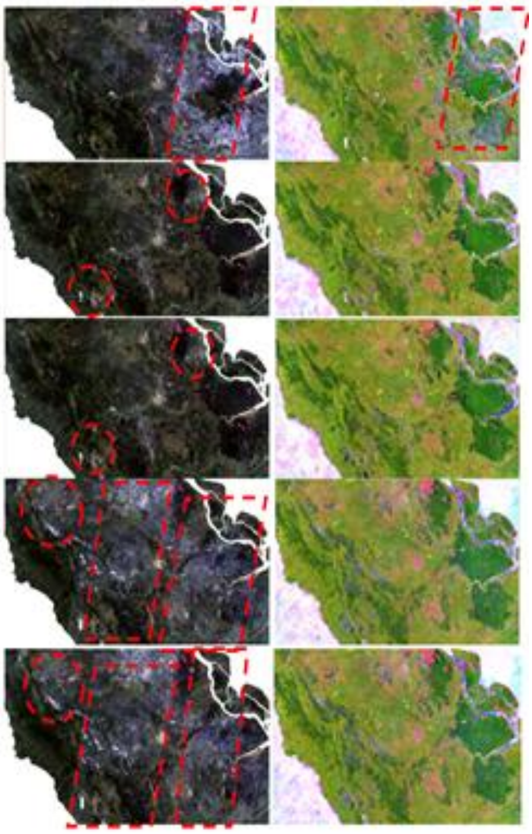

Figure 10. QL of MPB image from top to bottom (in sequence) the periods of 0,5 years; 1 year; 1,5 years; 2 years; and 2.5 years; the left images: RGB 432 and right image: RGB 654

Landsat-8 data were generally shown in the natural color combination image of RGB 432, which was a combination of 3 (three) visible red (band-4), green (band-3), and blue (band-2); and vegetation analysis image of RGB 654 which was a combination of red SWIR-1 (band-6), green NIR (band-5), and blue (band-4). Similarly, the generated MPB mosaic image in this process was also shown in RGB 432 and 654 band combinations. The analysis results with the MPB model is in line with the previous study developed by Kustiyo [21]. The image data were ready for further interpretation and classification processing for various application purposes.

As for the results the analysis of MPB images 2015 and 2017, there were still small clouds and haze spread in some places, as shown in the red circle mark (east of Riau region). Its indicate that there was no clear pixel among the data sets used, meaning that the weather conditions in the study area of the year were relatively cloudy and hazy.

A due to the analysis using the above a MPB model with annual data variations has not produced a quality image, we tried the analysis using a MPB model with semi-annual data variations, with the result was shown in Figure 10. From this figure, it can be concluded that the MPB model with semi-annual data variations of a half years, 1 year, 1.5 years, 2 years, and 2.5 years have produced more sufficient results to eliminate cloud cover. However, for haze quality was still needed to be eliminated further, especially on low spectral bands that was quite sensitive to atmospheric disturbances such as a blue band (band-2).

From the image analysis of the results of both the MPB model approach with the annual and semi-annual data, proving that the MPB model cannot be used for mosaicing cloud-free images, because it has not shown significant improvement in image quality results, both from minimizing cloud cover and haze point of views. For that reason, the MTB model was developed for the study.

### 3.3. Mosaic Tile Based (MTB)

In the processing of MTB model approach, the above same data were grouped into 3 (three) tile sizes of 0.10; 0.05; and 0.02 degrees. The smaller the tile size the higher number of record tiles, the larger the data size, and the longer data processing time was needed, but the quality of mosaics will be higher.

From annual image mosaic analysis processed by MTB model, as shown in Figure 11 and Figure 12, it can be concluded from the left-to-right images that, the smaller the size of the tile the least cloud cover, and the thinner the remaining haze. But some small white clouds in still appear as shown in the orange circle sign (RGB 432) or white circle (RGB 654). Nevertheless, the decrease in cloud cover and haze due to tile sizes was occurring in all annual mosaic images generated from data on 2015, 2016 and 2017.

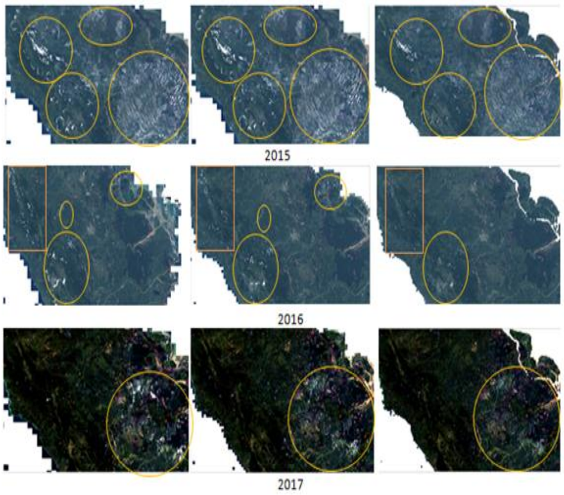


Figure 11. RGB 432 QL of annual image of mosaic tile based in three tile size (left to right) 0,1; 0,05; 0,02 degrees of 2015, 2016, and 2017

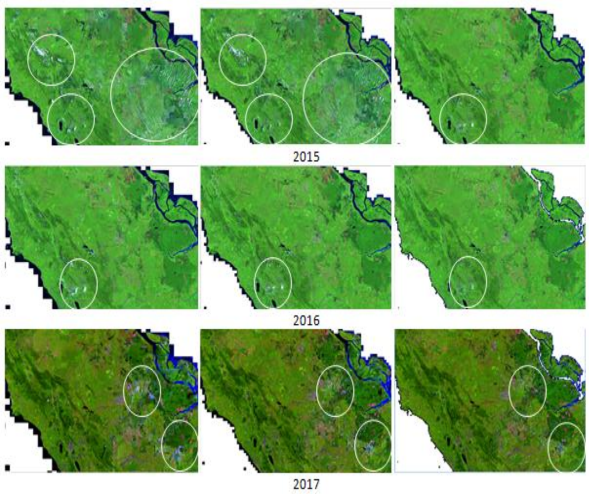


Figure 12. RGB 654 QL of annual image of mosaic tile based in three tile sizes (left to right) 0,1; 0,05; 0,02 degrees of 2015, 2016, and 2017

Analysis of MTB model results with different band combinations indicated that all RGB 654 images appear less cloud cover and haze rather than all RGB 432 images. Those less cloud cover and haze quality result due to tile size were occurring in all annual images generated from data on 2015, 2016, and 2017. Since the analysis with the annual data has shown firm results that the smaller the size of the tile the

least cloud cover, and the thinner the remaining haze, it was not necessary to do an analysis with semi-annual data.

The result of the percentage analysis of cloud cover and haze coverages of the final results using a formula (7), with various tile sizes of 0.1; 0.05; and 0.02 degrees from the path-row 128-59 of 2017 data was shown in Table 1. From the table it can be read that the percentage of clear area on column (9), ranging between 0 (total cloud cover) to 100 (cloud free), it appears that the smaller the tile size the higher percentage of the clear area which can be interpreted as the higher the quality of the tile.

The final annual mosaic image quality assessments were measured by cloud cover and haze using 5 (five) classes of clear areas. The clearer the mosaic image the higher the value or the better the image quality in terms of minimum cloud cover and haze. The result of the analysis (Table 2) shows that the application of MTB model with 0.02 degree tile size can produce the best image mosaic of minimum cloud cover and haze.

Table 1. The image quality score of each tile data year 2017 path-row 128-59 (10 tiles from the top left corner of the tile)

| File_Name (1) | LuasData (2) | LuasClr (3) | LuasDrt (4) | MaxSwirNir (5) | HazeInd (6) | NIRGRNInd (7) | SWIRGRNInd (8) | PrsCLR (9) |
|---|---|---|---|---|---|---|---|---|
| Tile size 0.10 degree | | | | | | | | |
| L8U1T128059m_060615_geo_nohaze | 51 | 0 | 83140 | 22 | 1 | 22 | 5 | 1 |
| L8U1T128059m_090815_geo_nohaze | 77 | 0 | 123377 | 16 | 1 | 16 | 10 | 1 |
| L8U1T128059m_090815_geo_nohaze | 55 | 0 | 89130 | 20 | 1 | 20 | 17 | 1 |
| L8U1T128059m_190415_geo_nohaze | 99 | 2 | 158875 | 22 | 27 | 23 | 20 | 75 |
| L8U1T128059m_050515_geo_nohaze | 100 | 31 | 160000 | 43 | 56 | 44 | 35 | 96 |
| L8U1T128059m_050515_geo_nohaze | 100 | 37 | 160000 | 36 | 54 | 37 | 28 | 96 |
| L8U1T128059m_260915_geo_nohaze | 100 | 27 | 160000 | 34 | 48 | 35 | 27 | 99 |
| L8U1T128059m_311215_geo_nohaze | 100 | 11 | 160000 | 29 | 19 | 31 | 31 | 40 |
| L8U1T128059m_090815_geo_nohaze | 91 | 33 | 146112 | 36 | 29 | 37 | 31 | 60 |
| Tile size 0.05 degree | | | | | | | | |
| L8L1T128059m_151116_geo_nohaze | 100 | 30 | 40000 | 34 | 50 | 38 | 37 | 98 |
| L8U1T128059m_080616_geo_nohaze | 100 | 23 | 40000 | 46 | 55 | 47 | 37 | 99 |
| L8U1T128059m_230516_geo_nohaze | 100 | 2 | 40000 | 35 | 60 | 36 | 30 | 100 |
| L8U1T128059m_230516_geo_nohaze | 100 | 4 | 39998 | 40 | 62 | 43 | 40 | 100 |
| L8U1T128059m_110816_geo_nohaze | 98 | 0 | 39479 | 25 | 34 | 26 | 23 | 90 |
| L8U1T128059m_110816_geo_nohaze | 81 | 0 | 32734 | 18 | 41 | 18 | 15 | 99 |
| L8U1T128059m_110816_geo_nohaze | 60 | 0 | 24171 | 27 | 37 | 29 | 26 | 98 |
| L8D1G128059m_011216_geo_nohaze | 53 | 2 | 21288 | 12 | 7 | 14 | 15 | 35 |
| L8U1T128059m_080616_geo_nohaze | 100 | 16 | 40000 | 46 | 54 | 48 | 38 | 100 |
| Tile size 0.02 degree | | | | | | | | |
| L8R1G128059m_180117_geo_nohaze | 100 | 0 | 6400 | 42 | 81 | 43 | 41 | 99 |
| L8LTP128059m_011017_geo_nohaze | 100 | 14 | 6400 | 1 | 100 | 1 | 1 | 100 |
| L8LTP128059m_130717_geo_nohaze | 100 | 0 | 6400 | 3 | 100 | 1 | 5 | 100 |
| L8R1G128059m_180117_geo_nohaze | 100 | 0 | 6400 | 37 | 92 | 39 | 38 | 100 |
| L8R1G128059m_030217_geo_nohaze | 100 | 0 | 6400 | 6 | 99 | 2 | 10 | 100 |
| L8R1G128059m_030217_geo_nohaze | 100 | 1 | 6400 | 5 | 97 | 1 | 8 | 98 |
| L8R1G128059m_070317_geo_nohaze | 100 | 0 | 6400 | 21 | 97 | 22 | 21 | 100 |
| L8R1G128059m_070317_geo_nohaze | 100 | 0 | 6400 | 55 | 91 | 56 | 50 | 100 |
| L8R1G128059m_070317_geo_nohaze | 100 | 0 | 6400 | 37 | 70 | 37 | 30 | 99 |

Note:
The image taken from the sample was only 10 (ten) tiles, in order from the top left-hand corner of the tile

| | |
|---|---|
| File_Name | : File Name |
| (L8UIT128059m_060615_geo_nohaze) | : Data Landsat-8; path-row 128-59; Date 6/06/2015; no haze |
| LuasData (%) | : The percentage of data area, percentage tile containing data of a full tile |
| LuasClr (%) | : The percentage of clear area (without cloud and haze coverage) |
| LuasDrt (%) | : Percentage of land area |
| MaxSwirNir | : Maximum ratio value between SWIR-1 value with NIR value |
| HazeInd | : Haze Index (c) = f (Blue, Red); c=2.7475*blue) |
| NIRGRNInd | : Vegetation confidence = NIR/Green Indeks |
| SWIRGRNInd | : Open land confidence = SWIR-1/Green Indeks |
| PrsCLR (%) | : Percentage of clear area (Final Score to Quality of Tile) Final_Score = a*Cloud Free+b*Haze Free+c*VegConv.+d*OpenLandConv (%) |

Table 2. Statistical analysis of Percentage of Clear Area (PCA) of mosaic image result of MTB

| PCA | | PCA tile 0,10 | | | | PCA 0,05 | | | | PCA 0,02 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Class | Range | 2015 | 2016 | 2017 | 3 Years | 2015 | 2016 | 2017 | 3 Years | 2015 | 2016 | 2017 | 3 Years |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| 1 | 0-70 | 46,09 | 15,50 | 35,60 | 5,01 | 40,69 | 11,98 | 31,06 | 3,86 | 35,22 | 10,20 | 28,81 | 3,00 |
| 2 | 71-80 | 10,69 | 7,01 | 6,41 | 4,34 | 8,69 | 4,82 | 5,18 | 2,76 | 7,11 | 3,06 | 3,62 | 1,56 |
| 3 | 81-90 | 12,42 | 12,96 | 8,48 | 8,48 | 11,02 | 9,22 | 8,55 | 5,91 | 9,29 | 6,33 | 6,43 | 3,77 |
| 4 | 91-95 | 9,49 | 15,10 | 11,29 | 13,96 | 8,69 | 11,57 | 8,47 | 8,69 | 7,38 | 7,51 | 6,55 | 5,28 |
| 5 | 96-100 | 21,31 | 49,43 | 38,21 | 68,20 | 30,90 | 62,41 | 46,74 | 78,78 | 40,99 | 72,90 | 54,60 | 86,39 |
| | | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |

Note: 3 years: best tiles from the data of 2015+2016+2017

The success in the development of MTB model can be visually shown by comparing a raw image to the result of the MTB image model, as shown in Figure 13. This MTB image shows the annual image data of 2016. The results of the analysis with MTB model could improve to obtain the quality appraisal of the image and efficiency of the analysis process toward the operational implementations in Indonesia that have been done by the previous researchers, institutions, and projects such as the TREES Projects [14], [23], [28], SLAT [10], [11], NCAS [13], INCAS [5], [15], CRISP [12], [29], University of Maryland [17], [19], [20], [24], [26], [30], LAPAN [21], and Humboldt University zu Berlin [22].

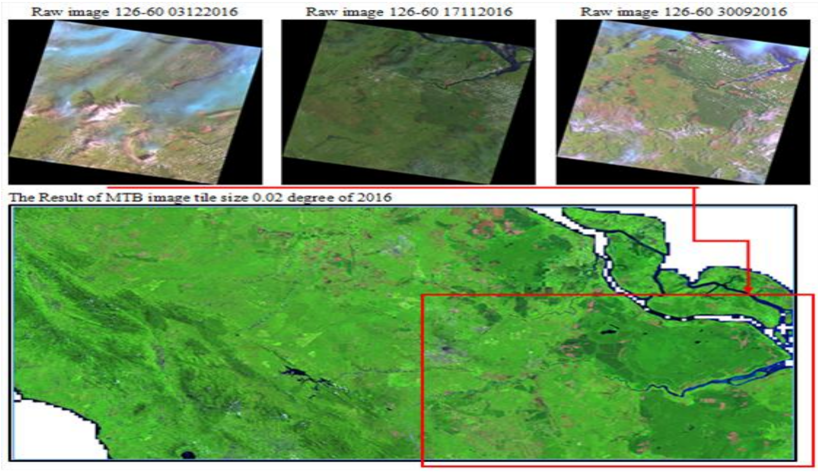


Figure 13. Comparison of clouded area of raw image and the result of MTB image 2016

## 4. CONCLUSION

The development of minimum cloud cover mosaic image of the Landsat-8 multitemporal data with MTB model was carried out at the central part of Sumatra, covering parts of Riau, West Sumatra, and North Sumatra Provinces. The satellite image data used was Landsat-8 OLI consisting of 5 (five) spectral bands (band-2 to band-6). The Landsat-8 OLI used includes 10 (ten) scenes of data on path-row 125-59, 125-60, 126-59, 126-60, 126-61, 127-59, 127-60, 127-61, 128-59, and 128-60, with a total of 478 scenes. In each year, each scene was recorded as much as 23 times recording (acquisition date). The data used were recorded for 2.5 years, starting from January 2015 to June 2017.

This paper has produced an annual minimum cloud cover mosaic image of the Landsat-8 OLI multitemporal data, developed with MPB and MTB models. Both mosaic images of MPB and MTB models were developed for the purpose of digital analysis, since they were processed without changing the reflectance value. The MPB mosaic imagery was processed based on the minimum cloud pixel value, while the MTB mosaic image was processed based on the best quality of each tile or pixel group. The result of the analysis shows that processing of mosaic image with MPB model produces optimal mosaic image with one year data set. While the MTB model of the tile size variability produces an optimal mosaic image. From the comparison of mosaic image of MPB to MTB processed by applying the formula shows that the MTB image was better and can be measured the quality of cloud cover and haze.

The MTB model in this paper was applied with a tile size of 0.1 (11x11 $km^2$); 0.05 (5.5x5.5 $km^2$); and 0.02 (2.2 x 2.2 $km^2$) degrees. The results show that the smallest tile size of 0.02 provides the best result, that was the clear area percentage of cloud cover and haze. Comparison of clear area percentage with cloud cover and haze, for 3 years (2015, 2016, and 2017) for three mosaic images of MTB with tile size of 0.10; 0.05, and 0.02 degrees, were 68.2%, 78.8%, and 86.4%, respectively. This reflected the quality of MTB which means that the smaller the tile size, the higher the percentage of clear area, the higher the quality of the resulting mosaic image.

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